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A New Play-off Approach in League Championship Algorithm for Solving Large-Scale Support Vector Machine Problems

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KEYWORDS

Support Vector Machine;
League Championship Algorithm;
Quadratic Optimization;
Large-Scale Optimization;
Met heuristics.

ABSTRACT

There are numerous methods for solving large-scale problems in which some of them are very flexible and efficient in both linear and non-linear cases. The League championship algorithm is such an algorithm which may be used in these types of problems. In the current paper, a new play-off approach will be adapted to league championship algorithm for solving large-scale problems. The proposed algorithm will be used for solving large-scale support vector machine model which is a quadratic optimization problem and cannot be solved in a polynomial time using exact algorithms or effectively using traditional heuristics. The effectiveness and efficiency of the new algorithm will be compared to traditional one in terms of the quality and computational time measures.

1. Introduction[1]

There are numerous algorithms, for solving large-scale problems which are very efficient for finding near optimal or in some cases exact optimal solution. As a part of them, met heuristics are used for solving hard optimization and NP-Hard problems [1]. Because of their generality, they make few assumptions about the model means that are very capable for solving a variety of problems [2]. Therefore, many researchers have published papers propose new or modified met heuristics for improving the performance of the algorithms. For example water cycle algorithm [3] and bat-inspired algorithm [4] are two new met heuristics. In this area, case studies and applications are considered also [5- 7].

In addition to the above, met heuristics are very useful for solving engineering problems such as project scheduling [8], Shortest path [9], supply chain management [10], Linear regression [11] and etc.

Support vector machine (SVM) is one of the mentioned problems which can be solved using the met heuristics, especially in the case of large scales [12] in both parameter setting and model selection field [13].

In this paper a new play-off approach will be considered on a traditional met heuristic, say league championship algorithm (LCA) inspired of sport leagues which may improve the performance of the algorithm in terms of the optimality and time measures. This contribution intends not only to reduce the number of iteration of the algorithm but also meliorate the best

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achieved solution. By the previous explanations, the rest of this research is outlined as follows:
All of the preliminaries about SVM and traditional LCA algorithm will be described in sections 2 and 3, respectively. The proposed approach will be prefaced and explained in section 4 which leads to a new modified LCA algorithm. Section 5 contains numerical computations using several SVM datasets in the case of large-scales. Finally, section 6 will be assigned to conclusion remarks.

2. Support Vector Machine (SVM)

In machine learning, the term Support vector machine refers to a classification technique which aims at finding a separator hyper plane for classifying data [14]. SVM attempts to find max-margin hyper plane because of its generalization aspects (Fig. 1). Since each hyper plane divides own space to two half spaces then SVM is used for two group classification problems. This basic model called binary SVM. Training a SVM model needs to solve the quadratic optimization model as below:

$$
\begin{aligned}
\min_{\omega,\xi,b} \quad & \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \\
& y_i\left(\omega^T X + b\right) \ge 1 - \xi_i \quad i = 1,2,\dots,n \\
& \xi_i \ge 0
\end{aligned}
\tag{1}
$$

Where, ω, b are the normal vector and biasness of the separator hyper-plane, respectively. ξ_i\`s are penalty variables. Also, $X$ is the data matrix contains $n$ train data. Finally, $y_i$\`s are binary variables which considered equal to 1 for all data belong to class 1 and 0 for all belong to class -1.

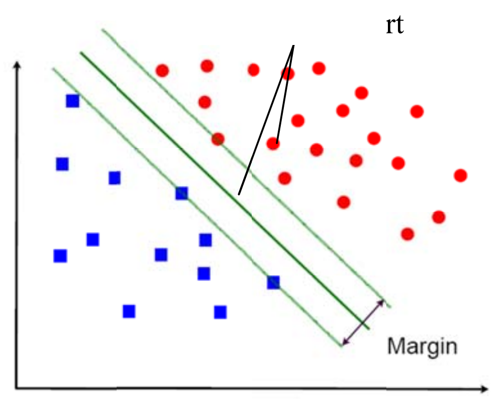


Fig. 1. Separating hyper plane with maximum margin

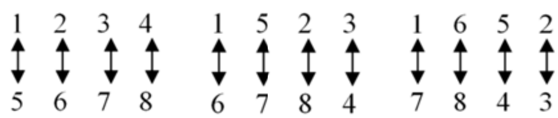
Solving model (1) is called as training SVM in the literature. There are many efficient methods for training SVM some of them are very useful and efficient in the case of large-scales [15- 16].
In this paper a new approach will be combined with a met heuristic algorithm, discussed during the next sections for solving large-scale support vector machine problems.

3. League Championship Algorithm and Play-off Approach

League championship is a population based algorithm mimics the sport leagues for improving the generated population to access an optimal or a near optimal solution [17]. There can be found some applications of this algorithm in the literature. For example, Algerian power system network has been optimized using LCA [18]. In another work, LCA is used to design pressure vessel and welded beam [19]. The introduced researches, affirm the superiority of LCA comparing to some other met heuristics.
For more description of the algorithm, Assume that there is a sport league of size L meaning that L teams aim at becoming a champion at the end of the season. This sport league terminates after S seasons. Also, assume that each team is assumed to have n players. Regarding such a league, each team has L-1 matches during a season and S×(L-1) matches all over the seasons. It is logical to assume that a strong team beats a weak. However, such beating may not be happened. The more logical statement is that a strong team has more chance to beat the weak one. After a match ends, each coach analyzes own team performance to detect the strength and/or weaknesses, known as SWOT analysis. According to the LCA terminology, we can match the sport league terms to the evolutionary algorithm. "League" stands for the population of the solutions in which the "team *i*" is the *i*th solution in the population. Each "week" in a season refers to "iteration". Also, "playing strength" is considered as "objective function value" and "a new formation" can be interpreted as "a new solution" [20].
The current algorithm has four main steps as follows:

A) Generating and scheduling a league

Since LCA is population based algorithm, it needs to generate a population of solutions vector at the first. Then, each generated individual vector will be considered as a team, while each element of the vector may be corresponded to a player in a team. In the other hand, a football league with *L* teams is equivalent to an optimization problem with 11 variables which to be solved by LCA using a population of size *L*. A single round-robin schedule is utilized where each team plays every other participant once in each season. For a league of size *L*, a single round robin tournament requires $L\times(L-1)/2$ matches and for odd number of teams a team has no match in each week. For scheduling matches, a number can be assigned to each team and the first week matches can be scheduled by pairing them off. Then for the next weeks, consider one team fix and rotate other teams clockwise. Figure 2 shows the scheduling process for an 8 team league.



(a) (b) (c)

Fig. 2. A scheduled league with size *n* =8: (a) first week (b) second week (c) third week

Note that, if *L* is odd, then a dummy team may be added to the league. It means that in each week a team gets rest. LCA continues for *S* successive seasons and thus for a single round robin league of size *L*, the number of matches is equal to $S\times(L-1)$.

B) Winner and loser Recognition

In a sport league, each team may be scored considering the result of played match. It is reasonable that a powerful team with more strength beats the weaker one. But, the loose of the mentioned team is also possible. So, for simulating the winner/loser recognition rule in the algorithm the value of the objective function is considered as the team strength. Then, the distance between best obtained solution (in terms of objective function) and strength for each team can be computed and the win probability for team *i* derived by equation at below:

$$\frac{f\left(x_j^t\right)-\hat{f}}{f\left(x_i^t\right)-\hat{f}}=\frac{p_i^t}{p_j^t} \qquad (2)$$

Where, $f\left(x_i^t\right)$ is the value of objective function corresponding *i*th team at week *t*, $\hat{f}$ shows the best obtained objective function and p_i^t is the probability of team *i* win the match at week *t*.

When p_i^t was computed, a uniform random number will be generated to determine the winner team. The team *i* wins game if the generated number is less than p_i^t and loses if it is greater. By this described approach, the winner team can be determined and scores may be assigned to the winners teams.

C) SWOT analysis

After running all matches, the games will be analyzed for determining strengths, weak, opportunities and threats. This investigation may leads to a better team formation. In LCA algorithm it is essential to determine that how this analysis can be implemented. Table 1 illustrates this approach considering the notations at below:

- *j*: index of the team that has played with team *i* at week *t*.
- *k*: index of team that has played with team *l* at week *t*.
- *l*: index of team that will play with team *i* at week *t* +1.

Tab. 1. the SWOT analysis in different situations

	k: winner l: winner Focus on…	k: winner l: loser Focus on…	k: loser l: winner Focus on…	k: loser l: loser Focus on…
S	*Own strengths (or weaknesses of j)*	*Own strengths (or weaknesses of j)*		
W			*Own weaknesses (or strengths of j)*	*Own weaknesses (or strengths of j)*
O		*Weaknesses of l (or strengths of k)*		*Weaknesses of l (or strengths of k)*

T	*Strengths of l (or weaknesses of k)*	*Strengths of l (or weaknesses of k)*

According to the obtained results for teams i, j and k, a new formation may be considered for each team considering the opponent at the next match. This reformation causes a new solution after each iteration. The next step will describe this procedure.

D) Team reformation

This step is an extraction which is possible after doing step C. each team attempts to improve own characteristics by busing the results extracted from SWOT analysis. In this regard, four different conditions are possible. Each of them requires a specific reformation:

- i winner, l winner:

$$x_{id}^{t+1} = \lambda b_{id}^{t} + (1-\lambda) y_{id}^{t} \left(c_1 r_1 \left(x_{id}^{t} - x_{kd}^{t} \right) + \left(c_1 r_2 \left(x_{id}^{t} - x_{jd}^{t} \right) \right) \right) \tag{3}$$

- i winner, l loser:

$$x_{id}^{t+1} = \lambda b_{id}^{t} + (1-\lambda) y_{id}^{t} \left(c_2 r_1 \left(x_{kd}^{t} - x_{id}^{t} \right) + \left(c_1 r_2 \left(x_{id}^{t} - x_{jd}^{t} \right) \right) \right) \tag{4}$$

- i loser, l winner:

$$x_{id}^{t+1} = \lambda b_{id}^{t} + (1-\lambda) y_{id}^{t} \left(c_1 r_2 \left(x_{id}^{t} - x_{kd}^{t} \right) + \left(c_2 r_1 \left(x_{jd}^{t} - x_{id}^{t} \right) \right) \right) \tag{5}$$

- i loser, l loser:

$$x_{id}^{t+1} = \lambda b_{id}^{t} + (1-\lambda) y_{id}^{t} \left(c_2 r_2 \left(x_{kd}^{t} - x_{id}^{t} \right) + \left(c_2 r_1 \left(x_{jd}^{t} - x_{id}^{t} \right) \right) \right) \tag{6}$$

Where, d is the dimension index, r_1 and r_2 are uniform random numbers, c_1 and c_2 are constant used to scale contribution of retreat and approach components, respectively. Finally, b_i^t is the best achieved solution for ith team till week t.

Note that in original equations of LCA there is no parameter λ. This proposed parameter establishes a convex combination between best and current solutions and therefore can improve intensification/diversification by its different values. Figure 3 outlines a flowchart for LCA algorithm.

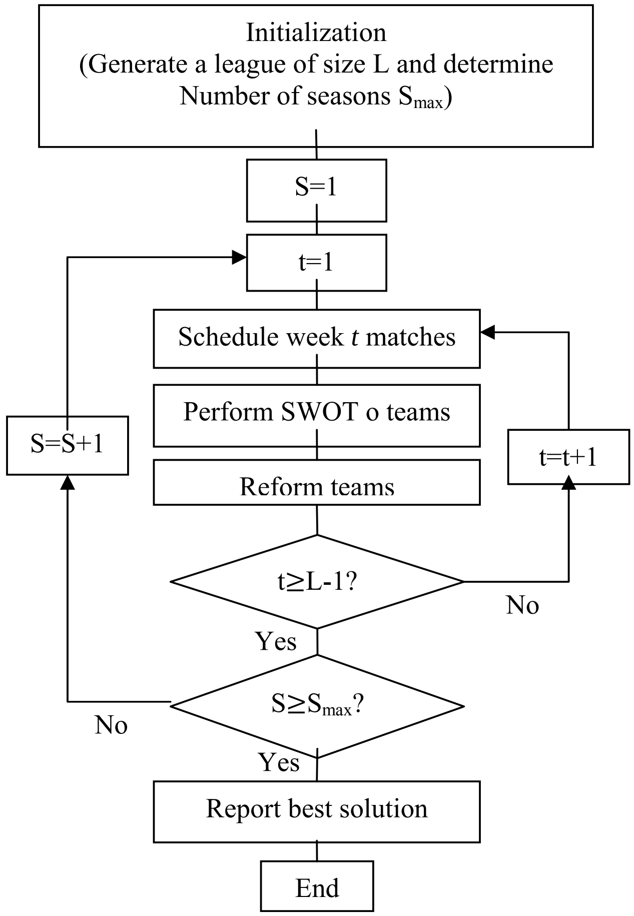


Fig. 3. Flowchart for traditional LCA algorithm

It is obvious that the number of replaced team may be considered as a parameter to be set. In this research we considered this parameter equal to 3 implies that 3 teams among of the lowest scored ones drop off at the end of each league. But, one can consider it as a parameter to be tuned or analyzed using sensitivity analysis techniques.

4- Numerical results

After describing the traditional LCA and proposed play-off approach it can be possible to solve some problems using the introduced methods. All results have been obtained using a system with 2.4full CPU and 2GB of RAM. The parameter λ is considered equal to 0.5 in solving typical problems.

The datasets are randomly generated in large scale support vector machine area and solved 10 times for computing mean CPU time and also best achieved objective function. Table 2 shows an outlined report about the size of problem and the obtained solution.

Tab. 2. A comparison between LCA and Play-off LCA using some random generated datasets (S_{max}=10, L=18)

Dataset	Size	Traditional LCA			Play-off LCA		
		Num of Seasons	Best Solution (Accuracy)	CPU Time (Seconds)	Num of Seasons	Best Solution (Accuracy)	CPU Time (Seconds)
1	1000×20	8	76%	50	5	76%	43
2	2500×35	7	65%	218	5	65%	175
3	4000×29	9	69%	290	5	69%	232
4	5000×44	10	78%	552	6	78%	438

5	10000×39	10	59%	975	8	63%	749
6	15000×51	10	91%	1912	7	91%	1532
7	23000×13	10	87%	747	8	90%	598
8	30000×26	10	79%	1950	8	79%	1549
9	50000×71	10	63%	8875	8	78%	7089
10	75000×48	10	70%	9123	7	70%	7142

It is obvious that the play-off approach outperforms traditional one in terms of accuracy and CPU time. The improvement comes from this fact that traditional LCA has not enough intensification which may not be efficient enough to converge optimal solution comparing to the expulsive scheme. Therefore, adding new teams season by season tackles this limitation and hence lead to a faster algorithm. For demonstration, Figure 5 compares traditional LCA versus play-off one, graphically. It can be concluded that if the size of problem increases, the play-off approach shows better performance comparing the old algorithm in terms of accuracy and also CPU time.

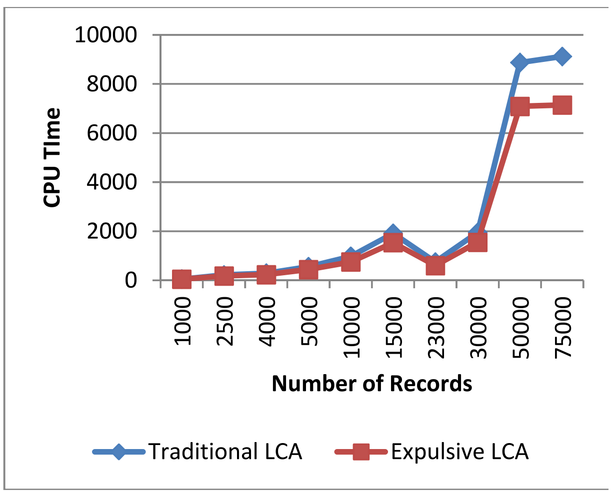


Fig. 5. Comparing the CPU time for traditional and play-off algorithm

One of the parameters which can effect on the achieved results is the convex coefficient λ. The value of this parameter determines the intensification/diversification of the algorithm in the other hand, the greater λ, the more intensified algorithm is. The less value of this parameter also leads to a more diversified algorithm. Table 3 illustrates a comparison for proposed algorithm under different value of λ using datasets.

Tab. 3. Comparing the accuracy using different values for λ in play-off algorithm (%)

λ / Dataset	0.1	0.2	0.4	0.5	0.7	0.9
1	76	73	76	75	74	72
2	65	64	63	64	63	60
3	69	69	69	68	67	64
4	73	78	73	77	76	74
5	60	62	62	62	63	58
6	81	89	91	90	89	88
7	90	90	90	89	88	87
8	71	73	71	79	77	75
9	75	78	76	77	76	74
10	59	65	70	69	68	65

In the semi large-scale datasets small to medium values for λ is better, while in the large-scale cases the small values of λ is not efficient. Because in the current conditions, there is not enough intensification when the value of λ is small. Generally speaking, there are not considerable variations in the accuracies under the various values of λ. Such an occurrence comes from this fact that SVM model is convex and therefore no local optima trap is confronted. Note that, the obtained results for different λ`s has trivial variations; however after using them to classify data the accuracies show more variations because of the data sensitivity.

5. Conclusion

This paper addressed a new approach called play-off in league championship algorithm. The main contribution of this approach was considering the dropping off for each last ranked team at the end of each season. Using this approach it was showed that the number of iterations and CPU time can be improved during the experimentation. Also a sensitivity analysis was conducted on the convex combination parameter and the results were interpreted. All of the experiments showed the superiority of the proposed method versus traditional one.

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